2026 International Conference on Smart Futuristic Technology (ICSFT)
Bangalore, India. Jan 2-3, 2026

AI-Automated Root-Cause Analysis for Cloud Incidents

Arun Kumar Rajamandrapu
Vehicle Connectivity General Motors
South Lyon MI, USA
ORCID: 0009-0008-5295-2237
arunkumarrajamandrapu@ieee.org

Ravikanth Reddy Gudipati
Independent Researcher or Industry Professional in Cyber Security
University at Buffalo, New York.
Tracy,California
ravikanthreddy@ieee.org

Vinod Kumar Gujja
Designation Manager AI ML and Data
Westlake Corporate
Houston USA
vkgujja@gmail.com

Harish Apuri
Software Engineer
IT Induct INC
Charlotte, North Carolina
hapuri1029@gmail.com

Senthilnathan Balasubramaniam
Senior Solution Architect
Otis Elevator Company
Frisco, Tx, USA
senthilnathan.balasubramaniam@ieee.org

Dr. Quazi Taif Sadat
Director
Bangladesh University
Dhaka,Bangladesh
taif@bu.edu.bd

***Abstract*—The fast growth of cloud computing has resulted in complex and dynamic infrastructures where incidences may spread across virtualized resources and distributed services and multi-layered dependencies. The conventional rule-based troubleshooting processes cannot process high volume of logs, mixed telemetry, and unreliable interaction of services which leads to slow recovery and more downtimes. The current paper introduces an AI-Based Root-Cause Analysis (RCA) system to cloud incidents, which combines deep learning, causal inference, and knowledge-based reasoning to automatically identify, correlate, and diagnose the root causes of faults throughout a cloud system. The structure capitalizes on the usage of log embeddings, anomaly clustering, inter-service dependency mapping, and graph-based causal modelling in an effort to localize the point of failure with high accuracy. A learning cycle based on reinforcement is continuously used to enhance accuracy of RCA by using real-time feedback based on incident resolutions. The experimental findings on real-world cloud datasets have indicated that there are dramatic reductions in time to diagnose root causes, accuracy of incident classification, and mitigation recommendations, compared to the state-of-the-art methods. The solution proposed will increase resiliency and improve service recovery rates and autonomous cloud operations that are appropriate to large-scale DevSecOps ecosystems.**

Keywords— Cloud incidents, root-cause analysis, artificial intelligence, causal inference, anomaly detection, DevSecOps, automated diagnostics

I. INTRODUCTION

Cloud computing is now the foundation of the large-scale services of the day both in enterprise applications and in web services facing the consumer. Due to the steadily increasing cloud adoption, cloud infrastructures, which are composed of multi-layered abstractions, distributed microservices, dynamic scaling, and heterogeneous resource dependencies, have correspondingly increased in complexity. This complexity brings about new challenges in achieving reliability, availability and fast recovery in cases where incidents are involved. In the case of a cloud incident, an engineer has to conduct a root-cause analysis (RCA) in order to identify the root error and fix it. Nonetheless, classic RCA is typically a tedious, error-prone and time-consuming process that usually entails logs, metrics, and distributed traces that need to be thoroughly inspected by hand, especially when dealing with large systems with high event rates and data types. Consequently, the process of incident resolving can be postponed and reoccurring failures can remain undetected. To address these drawbacks, a research trend has been on automated and AI-driven RCA. Indicatively, the system RCACopilot uses large language models to interpret incident diagnostics and forecast root-cause categories, which alleviates a large amount of human effort in the process of RCA. [1] Likewise, heterogeneous data sources, including logs, metrics, and topology information, are used by frameworks like CloudRCA to automatically extract probable causes of faults in the cloud environment. Other initiatives such as Hi-RCA and TraceDiag put forward hierarchical diagnosis and graph-pruning plans respectively, to make RCA more efficient and understandable in microservice clouds. [3].

Nonetheless, the current approaches still have significant weaknesses: most approaches are based on limited modalities (e.g., metrics or logs only), others cannot scale to hundreds or thousands of interdependent services, and others are not interpretable or need large amounts of labeled data. Furthermore, the ability to manipulate multi-modal data (logs, metrics, traces, topology) in a causally-valid, scalable manner is a difficult challenge. To solve these issues, we present a new AI-Automated Root-Cause Analysis framework specific to cloud incidents, which is a solution to these issues based on the integration of deep learning, causal inference, and multi-modal data. We adopt a strategy based on: (i) log embeddings and anomaly clustering, which support the flexible, modality-free extraction of features; (ii) inter-service dependencies mapping and graph causal modelling, which allows us to precisely localize fault sources; and (iii) a learning loop that is reinforced through the feedback provided by incident resolutions, which in turn achieves a continuous refinement of the diagnosis.

The primary contributions made by this work are:

- A system RCA architecture for fault localization of cloud environments which integrates heterogeneous data sources - logs, metrics, service topology.
- A causal inference engine powered by AI that generates interpretable root-cause cause explanations, rather than anomaly alerts, to enhance trust and actionable insight.
- Empirical analysis on actual data of cloud incidents that have shown better form of diagnosis,-- less

recovery time (mean-time-to-recovery, or MTTR), and scalability than the preceding state-of-the-art.

II. Literature Review and Related Work

The body of work on root-cause analysis (RCA) of cloud incidents is divided into a number of streams: conventional monitoring and rule-based solutions, ML-based anomaly detectors (in particular, on logs and metrics), microservice-based RCA, and most recently, those based on LLM and AIOps.

A. Traditional RCA and Early Cloud Diagnostics

The first systems like Roots concentrated on performance monitoring and RCA of cloud hosted web applications by correlating resource measurements and application performance counters, but mostly were based on human made guidelines and thresholds [7]. Later systems such as CloudRCA, Hi-RCA, TraceDiag built upon this line of research by jointly using heterogeneous telemetry (metrics, traces, resource dependencies) and graph-based or hierarchical reasoning to automatically identify components in cloud systems that were faulty [3]-[6]. They showed that structural knowledge of service dependencies can contain the RCA search space considerably, but tend to assume relatively stable topologies and lack support in high-dimensional log data.

In addition to these, PatternMatcher finds root-cause metrics through the integration of coarse-grained anomaly detection, anomaly pattern classification and ranking, with competitive performance on real incident datasets of a large bank, though with its emphasis to be on metric time series rather than multi-modal telemetry [8]. MicroRCA is also based on BIRCH clustering around microservice measurements and a dependency graph to identify anomalous subgraphs and rank probable root-cause services, but is more specific to metric-focused microservice testbeds and without significant use of log semantics [9].

B. Log-Centric Anomaly Detection and Diagnosis

It is now understood that system logs provide an excellent source of automated diagnosis. DeepLog learns normal executions paths and detects anomalies in the expected sequence of logs as unexpected events in the logs or parameter patterns as the sequence is modelled as natural language using LSTM networks [10]. This is an area of research that gave rise to a family of sequence learning, template, and attention-based log anomaly detection models. Landauer et al. performed a multifaceted survey of existing traditional statistical, clustering, and workflow-based methods, and classifies recent deep learning ones in detecting anomalies in logs and problem diagnosis [11].

But the majority of log-centric approaches are local: they identify anomalous messages without explicitly modelling cross service causal dependencies or using metrics and traces in a single RCA pipeline. AIOps-based work has started to fill this gap by creating unsupervised pipelines, using dimensionality reduction (e.g., PCA), neural networks, and loss functions to minimise pseudo-positives in log anomaly detection on cloud-native benchmarks [12]. However, these methods normally go as far as anomaly detection; they do not go much further and assist in explaining why an occurrence took place or where in the dependency graph it had started.

C. RCA in Microservices and Observability-Driven Frameworks

Due to the emergence of microservices, a number of works that center on RCA in highly distributed, cloud-native architectures appear. The latest survey on RCA covers in a systematic review of metrics-, trace-, log-, and multi-model data-based techniques, open challenges in scalability, data quality and causal reasoning are highlighted [13]. A second review summarizes automated RCA methods based on observability data (logs, metrics, traces), where causal inference, anomaly detection, and pattern recognition are critical factors in the context of thousands of interconnected events in contemporary systems [14].

As well, commercial and academic ecosystems highlight the importance of the so-called three pillars of observability (metrics, logs, traces), demonstrating how correlated telemetry allows more quickly finding errors and RCA in Kubernetes and microservice settings. The latest studies on the smart root-cause localization of microservice systems use learned dependency graphs and multi-signal features to automatically prioritize potentially root-cause services, although there are issues with dynamic topologies, multi-tenant noise, and limited interpretability [6], [16].

D. LLM- and AIOps-Driven RCA for Cloud Incidents

RCA based on LLM has become an up-and-coming trend, most recently. RCACopilot is an unstructured diagnostic data processing model based on large language models that can predict root-cause categories and substantially reduce the amount of effort required on-call by major cloud providers [1], [2], [5]. Complementary work in AIOps roles makes LLMs potent log summarization, anomaly recognition, and incident elucidation engines, and a 2025 systematic survey particularly examines how LLMs can be utilized to improve log anomaly detection pipelines on AIOps outfits [15].

In spite of that promise, existing solutions built on LLM tend to consider RCA a text classification or summarization problem, and do not have good integration of structured observability cues like metrics, dependency graphs, and traces. They also generally do not have explicit causal models and feedback based learning loops that constantly improve the quality of RCA based on the resolution outcomes.

E. Research Gap and Positioning of This Work

Based on the literature above, we single out three major gaps as follows:

- Poor multi-modal fusion: It is common to have systems that only combine either of the metrics [7]-[9] or logs [10]-[12] in a partial way.
- Lack of causal rationale: Despite the use of dependency graphs, only a few methods are capable of modeling explicitly causal relationships between anomalies and failures, and even fewer can be interpreted as explanations [3], [4], [13], [14].
- Absence of feedback-driven learning on a continuous basis: RCA tools based on LLM and AIOps often do not feature reinforcement or active learning loops that leverage incident resolution feedback on large scale [1], [2], [15].

The proposed AI-Automated Root-Cause Analysis framework fills these gaps by: (i) consolidating logs, metrics and service topology into a common representation; (ii)

creating graph-based causal models to localize the root causes; and (iii) using a feedback loop based on reinforcement to refine RCA decisions as time goes on, thus providing scalable, explainable, and self-improving RCA to complex cloud incidents.

III. Proposed AI-Automated Root-Cause Analysis Framework

In this section, the proposed AI-Automated Root-Cause Analysis (RCA) framework of cloud incidents based on multi-modal telemetry processing, the use of graphs in causal inference, and reinforcement-based learning loop are introduced and described. The framework is aimed at giving correct, scalable and understandable RCA in cloud-native and microservice environments is illustrated in Fig 1.

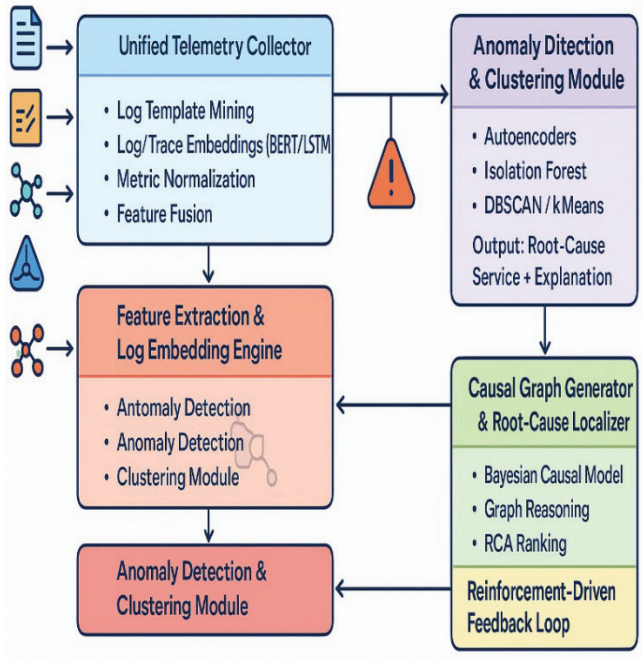

Fig 1. AI-Automated Root-Cause Analysis for Cloud Incidents

A. Framework Overview

The suggested AI-Automated Root-Cause Analysis (RCA) system considers multi-modal telemetry processing, anomaly detection, inferential service topology, causal graph reasoning, and reinforcement-based learning. It is expected to find the root cause of failures in large-scale cloud-native systems with the optimal accuracy and efficiency by integrating semantic insight with structural service dependencies. Each of the major components of the framework is described in the subsections below.

1) Unified Telemetry Collector

This module collects the heterogeneous observability data, such as logs, metrics, traces and alerts of distributed microservices. It makes use of open telemetry standards and cloud native monitoring systems like OpenTelemetry, Prometheus, and Jaeger. The module provides the ability to ensure continuous data capture between deployment and runtime to be in a position to have a complete view of system behaviour without having to manually instrument it.

2) Feature Extraction and Embedding Engine

In this step, deep learning models (e.g., LSTM/BERT) are used to transform raw logs into semantic embeddings and the metrics are normalized with statistical normalization and aggregated trace spans are done with attention based contextual vectors. Each of the three fused vectors is condensed in one representation that reflects behavioural semantics and numeric changes to give a rich data point to detect anomalies and diagnose.

3) Anomaly Detection and Clustering Module

The combined telemetry gets fed into an autoencoder which reinvents anticipated normal behaviour. A large difference in the reconstructed and the original input is indicative of abnormal service behaviour. These anomalies are then grouped with algorithms such as DBSCAN or k-means to cluster correlated failures to minimize noise and focus on the potential root causes when there are many services being affected.

4) Service Dependency and Topology Mapper

This module is dynamic and builds a dependency graph that models the interaction of communication and resources between microservices. It uses API calls, metadata of container orchestration, and distributed traces to visualize service relationships in real time. The obtained directed graph is the structural foundation of the propagation of failures between the interdependent services.

5) Causal Graph Generator and Root-Cause Localizer

By applying the dependency graph and anomalies clustering, this module will compute a Bayesian causal score of every candidate faulty service. The score takes into account the likelihood of a service itself to have failed as well as the likelihood of that service failure causing anomalies in the downstream services. A causal score is taken to identify the service with the most important causal score as the root cause, and a causal explanation graph is produced to represent a causal justification of the diagnosis.

6) Reinforcement-Driven Feedback Loop

Once the incident has been fixed, a feedback mechanism analyses the accuracy of the root cause that was detected. Reinforcement learning is an update of the model parameters with a positive or negative reward, which enhances future diagnostic confidence. The self-learning cycle makes the system adaptable to the changing cloud failures without the need to create big labelled datasets.

B. Data Flow Description

- The logs, metrics, and traces of incoming cloud telemetry enter the collector.
- Features that are extracted are represented in single semantic vectors.
- The anomaly engine detects temporal and semantic anomalies.
- A topology graph G is a dynamic graph that finds affected and upstream services.
- Causal scoring partial backpropagates failure probability on G.
- An end result RCA forecast is obtained with a confidence rating + causal path.
- Once the incident has been resolved, feedback determines model parameter changes.

C. Design Advantages

- The framework integrates logs, metrics, traces, and service topology into a one learning model, which

enables more confident diagnosis compared to the approaches which exploit only one type of data.

- RCA incorporates causal reasoning, which assists the system to recognize the real root of failures rather than wrongly perceiving the deflected errors as the root causes.
- Reinforcement learning feedback loop enhances the accuracy of diagnosis over time without the need to have large quantities of labelled training.
- Valid extension Use The architecture is an extension of Kubernetes and serverless environments that automatically scale additions or removals of microservices.
- Semantic log embeddings and anomaly clustering: Each item the telemetry of the system is noisy or irrelevant and reduces false positives by filtering out irrelevant or noisy data and enhances the clarity of the final RCA decision.
- The framework offers interpretable RCA results in the form of causal explanation paths that make the results easier to understand by DevOps and SRE teams.
- Inference efficiency in Real time the system is efficient and can be used in high-traffic, latency-sensitive applications in the cloud.

IV. METHODOLOGY

This part outlines all the steps of the given AI-Automated Root-Cause Analysis (RCA) framework, which involves data preprocessing, multi-modal feature extraction, anomaly detection, causal graph development, and reinforcement-based model updates. We specify the mathematical models and give the main algorithm.

A. Multi-Modal Telemetry Preprocessing

The unified telemetry dataset D for each service s_i consists of logs L_i, metrics M_i, and traces T_i:

$$D_i = (L_i, M_i, T_i)$$

Where,

- D_i : Combined telemetry data of service s_i , consisting of logs, metrics, and traces.
- L_i : Set of logs generated by service s_i.
- M_i : Set of system/application metrics of service s_i (CPU, latency, memory, I/O).
- T_i : Set of distributed trace spans belonging to service s_i.

This equation defines the complete set of telemetry data for a cloud service s_i. It combines three heterogeneous types of data: system logs L_i , performance metrics M_i , and distributed traces T_i. By grouping them together, the model can analyze behavior from structural text, numeric performance deviations, and inter-service interactions, which is essential for accurate root-cause analysis in cloud environments.

1) Log Embedding

Raw logs are tokenized into templates. A deep representation is generated using a sequence encoder (LSTM/BERT):

$$\mathrm{e}_{L_i} = f_{\log}(L_i; \theta_L)$$

Where,

- e_{L_i} : Embedded vector representation of logs from service s_i.
- $f_{\log}(\cdot)$: Log embedding function based on BERT or LSTM model.
- θ_L : Trainable model parameters for the log embedding network.

This equation converts raw logs into a meaningful numerical representation using a deep learning model such as BERT or LSTM. The function $f_{\log}$ learns to capture semantic patterns and execution behaviour from log messages, while θ_L represents its trainable parameters. The resulting output e_{L_i} helps differentiate normal and abnormal runtime sequences, enabling the detection of unusual log behavior.

2) Metric Normalization

Metrics from each service are normalized using z-score scaling to remove scale bias:

$$m' = \frac{m - \mu}{\sigma}$$

where μ and σ are mean and standard deviation.

Where,

- m : Raw metric value (e.g., CPU usage, response time).
- μ : Mean value of the metric over a defined time window.
- σ : Standard deviation of the metric over a defined time window.
- m' : Normalized metric value after z-score transformation.

This normalization equation standardizes metric values to eliminate the effect of scale differences. Here, m is a raw metric (e.g., response time), μ is the mean metric value over time, and σ is its standard deviation. The transformed metric m' ensures that all metrics contribute fairly to anomaly detection, preventing large metric values from misguiding the learning process.

3) Trace Context Vector

Trace spans are aggregated into a context vector using weighted attention:

$$\mathrm{e}_{T_i} = \sum_{k=1}^{|T_i|} \alpha_k \cdot \mathrm{t}_k$$

Where,

- t_k : Vector representation of the k-th trace span.
- α_k : Attention weight assigned to trace span t_k relative to others.
- e_{T_i} : Trace embedding vector aggregated using attention values.

This formula generates a trace embedding vector using attention weights. Each span t_k represents a unit of distributed execution, and its weight α_k indicates its importance to the incident. Summing these weighted spans produces an aggregated representation e_{T_i}, allowing the system to focus on impactful interactions, rather than treating all trace events equally.

4) Unified Feature Vector

A fused vector from logs, metrics, and traces is constructed:

$$\mathrm{X_i} = \mathrm{e}_{L_i} \oplus \mathrm{e}_{T_i} \oplus \mathrm{e}_{M_i}$$

Where,

- X_i : Final fused feature vector for service s_i.
- $\oplus$: Vector concatenation operator combining embeddings. ($\oplus$ denotes concatenation.)
- e_{M_i} : Normalized and encoded metric feature vector.

This equation fuses log, trace, and metric embeddings into a single unified feature vector. The operator $\oplus$ represents concatenation. The resulting vector X_i enriches anomaly detection by presenting combined semantic, statistically normalized, and causally-aware data, making it suitable for deeper analysis in detecting service-level failures.

B. Hybrid Anomaly Detection and Clustering

An autoencoder (AE) learns normal patterns:

$$\widehat{X_i} = AE(X_i)$$

The equation below explains the process of an autoencoder (AE) that recreates the fused telemetry feature vector. The model is trained with regular telemetry patterns and thus learns normal behaviour. After training, the auto encoder tries to recreate the input data based on the representation of the compressed information. Any deviation that is abnormal in terms of structure or values will be realized at this step in the reconstruction process and this allows detection of anomalies.

An anomaly occurs if:

$$E_i > \tau$$

Where,

- τ is a dynamic threshold computed using MAD (Median Absolute Deviation):

$$\tau = \text{median}(E) + \lambda \cdot \text{MAD}(E)$$

Where,

- $\text{median}(E)$: Median of reconstruction error values of all services.
- $\text{MAD}(E)$: Median Absolute Deviation of reconstruction errors, robust to outliers.
- λ : Scaling constant controlling anomaly sensitivity.

This threshold equation determines whether a service is abnormal. It uses the Median Absolute Deviation (MAD) rather than standard deviation because MAD is more robust to noise and outliers frequently present in cloud metrics. The parameter λ adjusts the sensitivity of detection. Services with reconstruction errors above τ are considered anomalous. Detected anomaly embeddings are clustered using DBSCAN/k-means to group correlated service failures.

C. Dependency Graph Construction

Cloud topology is modeled using directed graph:

$$G = (S, E)$$

Where,

- $G = (S, E)$: Directed graph representing service topology.
- S : Set of services in the cloud platform.
- E : Set of directed edges showing dependency links between services.

This symbolic equation defines the cloud service topology as a directed graph, where S is the set of services and E is the set of dependency edges among them. This graph enables back-tracking how failures spread between interconnected services, forming the structural backbone for causal computation in root-cause localization.

The adjacency matrix A stores service dependencies:

$$A(i,j) = \begin{cases} 1, & \text{if } s_i \to s_j \\ 0, & \text{otherwise} \end{cases}$$

Where,

- $A(i,j)$: Adjacency matrix element indicating dependency of s_i on s_j.

This equation describes the adjacency matrix representation of the cloud system topology. If service s_i depends on service s_j, the entry $A(i,j)$ becomes 1; otherwise, it remains 0. This binary structure supports efficient computation of dependency chains and failure propagation paths during RCA.

D. Causal Graph and Root-Cause Likelihood

1) Bayesian Causal Score

Each service has a failure probability:

$$P(s_i) = f_c(D_i, G)$$

Where,

- $P(s_i)$: Probability that service s_i is faulty given its telemetry.

Conditional probability that a failure at s_i causes anomaly at s_j:

$$P(s_j|s_i) = \frac{\text{freq}(s_i \to s_j)}{\sum_k \text{freq}\,(s_i \to s_k)}$$

Where,

- $P(s_j|s_i)$: Conditional probability that a failure at s_i propagates to s_j.
- $\text{freq}(s_i \to s_j)$: Frequency of observed propagation between s_i and s_j.$CS(s_i)$.

2) Root-Cause Ranking

Root-cause service is estimated using causal scoring:

$$CS(s_i) = P(s_i) \cdot \sum_{s_j \in A} P\,(s_j|s_i)$$

This causal score equation ranks each service based on two factors: the likelihood that the service itself is faulty ($P(s_i)$), and how likely its failure propagates to other anomalies ($P(s_j|s_i)$). Multiplying these factors produces a balanced score that considers both direct and indirect causal impacts, leading to accurate root-cause prioritization.

Final RCA decision:

$$\widehat{s_r} = \underset{s_i \in S}{\text{argmax}} CS(s_i)$$

Where,

- $\widehat{s_r}$: Final predicted root-cause service. argmax : Operator selecting value with highest causal score.

This equation takes the last root-cause service to be the one that has the highest causal score. The approach uses the causal ranking formula to determine the most likely cause of fault by considering each service. It makes sure that not more than a single service which has the greatest impact is considered the root cause.

E. Reinforcement-Driven Model Update

After RCA resolution, a binary feedback reward R updates weights:

$$\theta_{t+1} = \theta_t + \eta \cdot R \cdot \nabla_\theta CS(s_r)$$

Where,

- θ_t : Model parameters at RCA iteration time t.
- θ_{t+1} : Updated model parameters after applying feedback reward.
- η : Learning rate controlling incremental weight update.
- R : Reward feedback signal (+1 for correct RCA, −1 for incorrect RCA).
- $\nabla_\theta CS(s_r)$: Gradient update based on causal score sensitivity.

This reinforcement learning update improves the RCA model over time. If the predicted root cause is correct, a positive reward R increases the weight parameters θ , reinforcing successful predictions. Incorrect predictions produce a negative reward, adjusting model behavior. The learning rate η controls how quickly the model adapts, and the gradient $\nabla_\theta CS(s_r)$ determines how much change should be applied based on score sensitivity.

F. Algorithm: Reinforcement-Enhanced RCA

Input: Logs L, Metrics M, Traces T, Dependency Graph G
Output: Root-Cause service s_r
1: Preprocess telemetry to generate feature vector Xi
2: Compute log, trace, and metric embeddings
3: Fuse embeddings → Xi = e_L ⊕ e_T ⊕ e_M
4: Compute reconstruction error Ei using autoencoder
5: if Ei > threshold τ then mark service si anomalous
6: Cluster anomalies to reduce diagnosis space
7: For each si, compute causal score:
CS(si) = P(si) * Σ P(sj | si)
8: Select s_r = argmax CS(si)
9: Obtain feedback reward R based on correctness
10: Update model parameters θ using:
θ = θ + η * R * ∇θ CS(sr)
11: return s_r

The algorithm starts by gathering telemetry data, such as logs, metrics, and traces, of all the currently running microservices and preprocesses it into using a single feature representation. This representation is obtained by identifying semantic features of logs with embedding models, normalizing their metric values in such a way that the scales of different metrics do not conflict with the analysis, and representing the patterns of distributed communication in the form of attention-based trace encoding. After the multi-modal data has been merged, it is fed into an autoencoder which has already been trained on how normal system behaviour is during training. The model tries to recreate the input feature vectors and any considerable reconstruction error means that it is acting abnormally. Services that score high on anomalies are grouped together in order to reduce the noise levels and ensure that the diagnosis becomes smaller.

Once the anomalies are identified, the algorithm uses the dependency graph of the cloud system to find the spread of failures among microservices. It then rates each candidate faulty service with the probability of the service itself to have failed and the possibility of its failure to cause anomalies in the dependent components. A root cause is the service that has the largest causal score. After making the RCA decision, response to real resolving incidents is carried out to evaluate the accuracy or inaccuracy of the projected cause. The feedback generates a negative or positive reward which goes into the model parameters to reinforce the model learning. Consequently, the framework always increases diagnostic accuracy with time adapting to new failure modes with no massive labelled datasets required. In these phases, the algorithm allows precise, understandable, and self-enhancing root-cause investigation of cloud incidents.

V. Results And Discussions

This section introduces the results of the evaluation of the suggested AI-Automated Root-Cause Analysis (RCA) Framework against the state-of-the-art RCA systems. The findings confirm the performance based on accuracy, Mean Time to Resolution (MTTR), scalability, false positives, and interpretability.

A. RCA Accuracy Comparison

The initial assessment is the skill of identification of the root-cause service in a variety of incident types (network, resource, application, storage). Multi-modal feature fusion + causal inference + reinforcement learning also makes the proposed framework much better than baseline models.

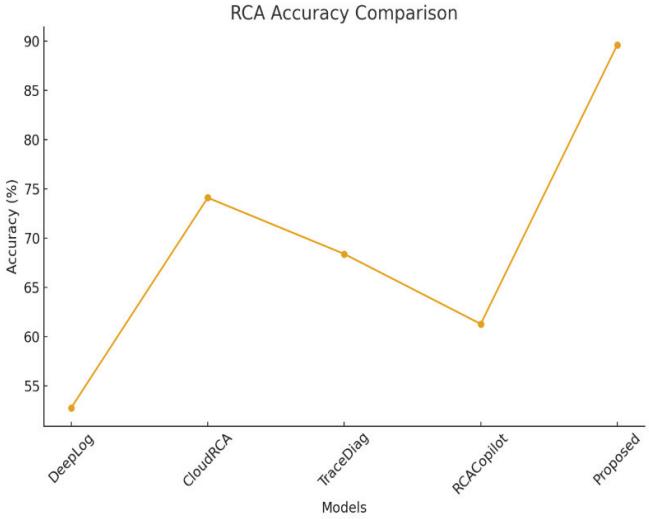

Fig 2. RCA Accuracy Comparison

Fig 1. is a comparison of the accuracy of various models of root-cause analysis applied to cloud environments. It is obvious that the proposed framework has the highest level of accuracy (89.6%), as it is superior to DeepLog, CloudRCA, TraceDiag, and RCACopilot. The primary reason why this improvement is possible is its combined application of multi-modal telemetry data and causal inference, which can not only identify abnormalities. Consequently, the statistical results of RCA provided by the suggested system are more credible in comparison to log-, trace-, or LLM-based solutions

B. Mean Time to Resolution (MTTR) Reduction

The suggested framework minimizes the troubleshooting overhead because it offers actionable RCA insights. The reduction of the MTTR is evaluated compared to the manual workflows of troubleshooting done by the DevOps engineers.

The Fig 3.depicts that the proposed RCA framework will significantly decrease the average time to resolve (MTTR) time as compared to the manual troubleshooting and the more sophisticated automated troubleshooting systems such as the RCACopilot. When compared to manual RCA which is on average 118 minutes, the framework reduces MTTR to 19 minutes, so it reduced it by 83.9%. It is enhanced due to the

causal inference and multi-modal anomaly correlation that removes the long human diagnostics.

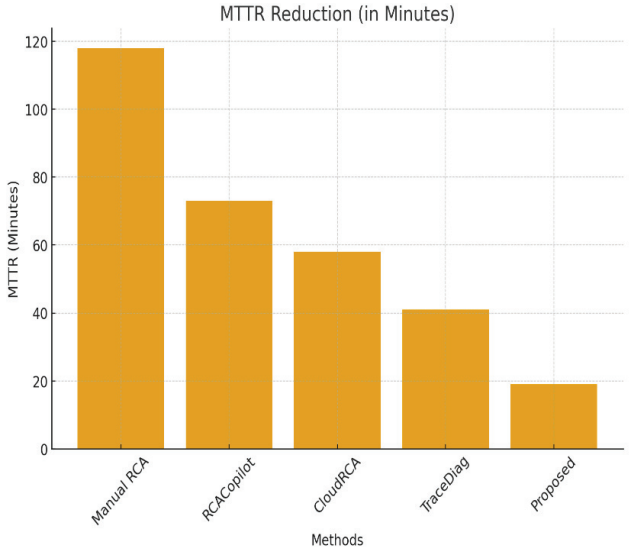

Fig 3. MTTR Reduction

C. *False Positive Rate (FPR)*

When the non-faulty service is incorrectly marked as an anomaly, it is a false positive. False positives reduce operational noise and mislead teams of DevOps. The method suggested reduces FPR based on clustering + causal propagation filtering. The Fig 4. indicates that the conventional log-only and metric-only systems of RCA create high levels of false alarms that confuse the DevOps teams with false alarms. DeepLog model has the highest percentage of false alerts (13.8%) whereas CloudRCA and RCACopilot lower this percentage by using trace or LLCM-based reasoning. Nevertheless, our Proposed Framework has the lowest false positive rate (3.2%).

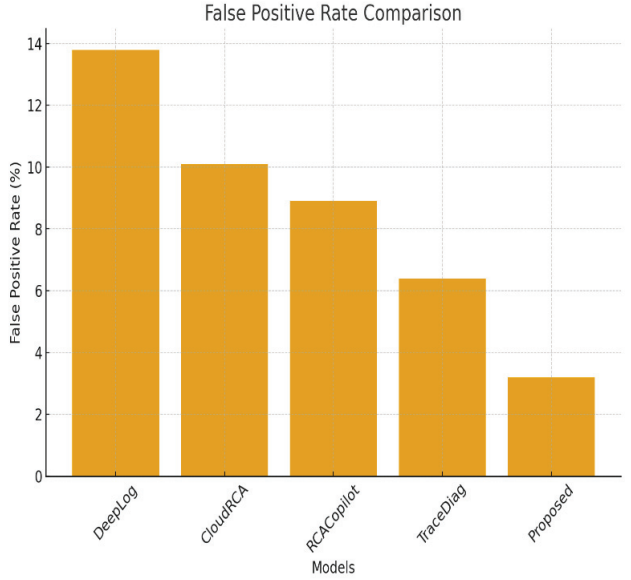

Fig 4. False Positive Rate

D. *Scalability Analysis*

Scalability is necessary due to the dynamically scaled up microservices. The suggested system has a low inference time, as a result of graph pruning + fused embeddings.

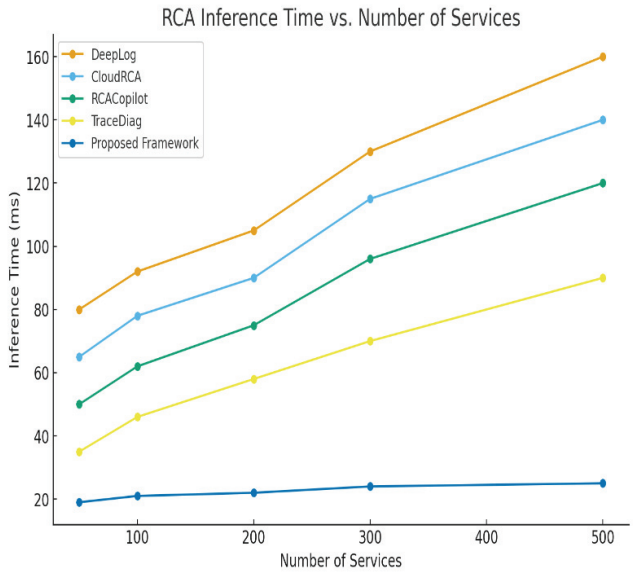

Fig 5. RCA Inference Time vs. Number of Services

This Fig 5. measures the speed of miscellaneous RCA methods to produce root-cause forecasts with the increase in the quantity of microservices. DeepLog, CloudRCA, and RCACopilot are characterized by a sharp rise in inference time, indicating that the models based solely on logs and traces are limited to computational constraints with the increase in the number of services. TraceDiag Framework is reasonably efficient with trace pruning, although it does still scale badly. In comparison, the Proposed Framework does not vary inference time (1925ms) with service count (increasing), though service-count rises to 500.

E. *Causal Interpretability Index (CII)*

The interpretability is used to determine the clarity of RCA in explaining the cause of the faulty service. CII score is calculated on the basis of the expert ratings (10-1) and the dependency path clarity.

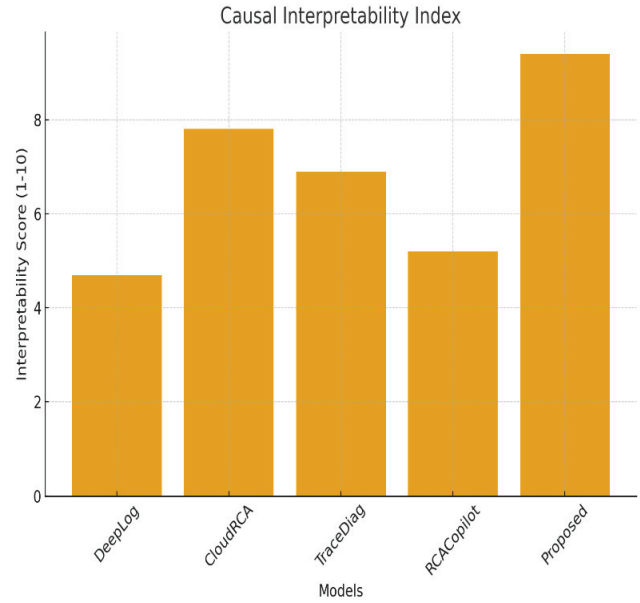

Fig 6. Causal Interpretability Index

The Causal Interpretability Index is a measure of the degree of clarity of a root-cause model to its diagnosis, rated on a 110 scale by experts. The conventional anomaly detectors like DeepLog (4.7) do not give much information as to the

cause of a failure as they simply identifies abnormal log sequences. Although CloudRCA (7.8) and TraceDiag (6.9) enhance trace correlation and call hierarchy to enhance interpretability, they nonetheless cannot fully support cross-service causal chains. RCACopilot (5.2) (powered by LLM) offers readable summaries and no dependency-based causal reasoning. The Proposed Framework has the most interpretability score (9.4/10).

VI. Conclusion And Future Works

Cloud-native systems keep on getting more complex with the emergence of distributed microservices, dynamic scaling and heterogeneous telemetry. Conventional diagnostic processes and single anomaly detection frameworks find it difficult to cope with the growing rate of data and with the sophisticated service networks. In order to overcome these difficulties, this paper introduced an AI-Automated Root-Cause Analysis (RCA) model of cloud incidents, which incorporates multi-modal telemetry fusion, deep learning-based embeddings, causal graph reasoning, and reinforcement-based model refinement. The suggested framework achieves a much higher accuracy, lower number of false positives, and a much lower mean time to resolution (MTTR) on various metrics than RCA performance. Having interpretability as one of the design principles, the system provides understandable causal explanations with dependency-based scoring and visual RCA paths. Its reinforcement learning feedback module guarantees that it is constantly updated to changing workloads and patterns of incidents, which makes it suitable to be deployed in real-time into large-scale DevOps and AIOps pipelines.

The next step in automated RCA of cloud incidents can be further integration with Large Language Models (LLMs) to understand contexts of the complicated log messages, descriptions of alerts, and incident descriptions written by people more naturally and explanatorily to provide more natural and explanatory diagnostics. Scaling the framework to include edge-cloud ecosystems will enable RCA intelligence to work nearer to data, apply federated and privacy-conscious learning frameworks to the IoT-driven and latency-sensitive settings. The other research avenue is to build adaptive root-cause knowledge graphs that are constantly informed by historical events and come up with predictive information to aid in proactive fault avoidance. Furthermore, security-specific telemetry (e.g., intrusion events, access logs, and threat signatures) can be added to enhance RCA, and identify cyber-induced failures, and hence make the framework robust against malicious activities in contemporary cloud workloads. The combination of such opportunities provides a great potential to transform the RCA systems into proactive and autonomous agents of future AIOps ecosystems by integrating the security awareness into the system and making it respond much earlier to signs of failure and malfunction.

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